Understanding Broadscale Wildfire Risks in a Human-Dominated Landscape

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ABSTRACT. Broadscale statistical evaluations of wildfire incidence can answer policy-relevant questions about the effectiveness of microlevel vegetation management and can identify subjects needing further study. A dynamic time series cross-sectional model was used to evaluate the statistical links between forest wildfire and vegetation management, human land use, and climatic factors in Florida counties. Four forest wildfire risk functions were estimated: one for fires regardless of ignition source, and three others for fires of specific ignition sources: arson, lightning, and accident (unintentional anthropogenic). Results suggest that current wildfire risk is negatively related to several years of past wildfire and very recent site prep burning, and risk is positively related to pulpwood removals. The effect of traditional prescribed burning on wildfire risk varies by ignition source. El Niño–Southern Oscillation (ENSO) sea surface temperature (SST) anomalies were also significantly linked to forest wildfire risk, but a measure of the wildland-urban interface was not significant. Although these county-level results hold promise for aggregate risk assessment, modeling at finer spatial and temporal scales might further enhance our understanding of how land managers can best reduce the longer term risk of catastrophic wildfire damages. For. Sci. 48(4):685–693.

Key Words: Vegetation management, wildfire production, wildland-urban interface, El Niño-Southern Oscillation.

THE 2000 WILDFIRE SEASON in the United States burned 3.5 million ha and resulted in federal direct suppression costs of nearly $1.3 billion (National Interagency Fire Center 2001). Many industry, environmental, and land management experts have attributed the extraordinary number of wildfires to decades of fire suppression on forests and rangelands of the West and other wildfire prone regions. Land managers and policy makers have proposed a number of actions that could reduce losses from catastrophic fires (USDA Forest Service 2000). Some of these proposals are controversial because they involve large increases in expenditures on wildfire suppression and vegetation management along with many policy recommendations for local and state governments and private landowners. Proposals include higher rates of prescribed burning, mechanical thinning, and timber harvesting than observed in recent years.

Wildfire and many of the measures to reduce wildfire risk have ecological, social, and economic implications, so research that effectively describes where, when, and why wildfires occur may enable more effective and forward-looking damage reduction strategies. Catastrophic wildfires affect the welfare of timber producers and consumers, disrupt

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the broader economy, destroy structures, and injure and kill people in affected regions (Bellinger et al. 1983, Butry et al. 2001). Such catastrophic risks can affect the timber management decisions of private landowners (Martell 1980, Routledge 1980, Reed 1984, Caulfield 1988, Valsta 1992, Yin and Newman 1996, Hesseln et al. 1998), so economic efficiency of timber production is dependent on an understanding of the factors that affect those risks. Vegetation management activities can also affect forest products producers as well as consumers by altering supply and demand conditions. Prescribed burning and changes in wildfire regimes affect the health of local residents through smoke emissions and the ecological conditions important to wildlife and water quality. Finally, wildfires and all kinds of vegetation management activities may affect net carbon emissions to the atmosphere (e.g., Kurz et al. 1991).

Thus far, recommendations on ways to reduce the aggregate costs and damages arising from wildfire have been derived from extrapolations from how fires burn at fine scales. This raises questions about how to extrapolate from fire behavior to fire risk and the appropriate scale of analysis. Fire behavior studies have been mainly fine-scaled, carefully controlled statistical analyses and simulations, providing insights into how factors such as fuel, wind, topography, and moisture affect fire behavior. This research has enabled a deep understanding of fire behavior, yielding tactically useful models such as BEHAVE (Anderson 1982, Andrews and Bevins 1999) and the FARSITE Fire Area Simulator (Finney 1998, Finney and Andrews 1999).

Fire risk, or the probability that a particular place on the landscape will experience a wildfire within a discrete period, is related to many of the same factors affecting fire behavior, but its assessment requires a different frame of analysis, one that relates wildfire to factors affecting wildfire risk over broader spatial scales and longer time scales (e.g., Donoghue and Main 1985, Keeley et al. 1999). While less common, this research would seek to relate wildfire risk to the activities of humans, land and vegetation characteristics, and weather patterns or climate. For example, research has shown that weather and climate factors related to the El Niño-Southern Oscillation affect broad scale wildfire risk over many parts of the United States (Brenner 1991, Barnett and Brenner 1992, Simard et al. 1985, Swetnam and Betancourt 1990).

Previous broad scale studies faced data and modeling constraints that prevented inferences about how wildfire risk was related to human activities, vegetation, and land use patterns. It is our contention that descriptors of land use patterns and other human activities such as vegetation management, which can modify the effects of weather and climate on wildfire risk, should be included in a more comprehensive statistical analysis of wildfire risk. Improving our understanding of human-fire interactions may facilitate more effective vegetation management and suppression planning in rural as well as in wildland-urban interface (WUI) settings—elevated human populations living in natural settings adjacent to population centers. It may also reveal the risk factors relevant to land use planning, fire resource decisions, and forestry or homeowner fire prevention incentives programs. Until we identify the individual effects of various kinds of human interventions on wildfire patterns in the presence of weather patterns or climate, valid evaluation of their trade-offs on large spatial and temporal scales is not possible.

The objective of this article is to analyze wildfire risks in a developed landscape at a longer time scale and a broader spatial scale than typically attempted. The statistical approach used here, which links fire probability to hypothesized explanatory variables at the county level of resolution, allows us to identify the individual effects of alternative strategies for reducing wildfire risks. The broad spatial scale of analysis, similar to that used in epidemiological studies, can identify the statistically most important factors contributing to wildfire risks and damages. It is also a means of isolating knowledge gaps and therefore potentially useful finer scale additional analyses. Another benefit of the broadscale modeling approach is to elucidate how the WUI in wildfire prone regions is related to wildfire patterns. Humans, through a variety of influences such as igniting fires, putting out fires, and altering land cover, are important factors shaping wildfire risk.

The subject of our analysis of wildfire risk is Florida, a human-dominated and vegetatively altered landscape prone to wildfire. Florida was once dominated by fire-dependent longleaf pine (*Pinus palustris* Mill.) and wetland and bottomland hardwoods, but it is now a heavily human-altered landscape with a mix of land uses and cover types that now also includes urban and suburban lands, agriculture, fragmented natural pine-hardwood forests, and slash pine (*P. elliottii* Engelm.) plantations. In the research presented below, we describe the specifications for our wildfire production functions and detail our statistical approach to estimating them. We discuss next the results of our estimates and conclude with comments about their policy and management implications and how future modeling could proceed.

Methods

Our approach to wildfire modeling follows theoretical discussions of wildfire production functions by Rideout and Omi (1990) and Hesseln and Rideout (1999). Hesseln and Rideout discussed the function in the context of economic optimization using control theory (see Silberberg 1990), in which such a function is a key consideration. While Hesseln and Rideout's analysis did not spell out an exact specification of a wildfire production function, it described an approach to thinking about land management in the presence of wildfire at broad spatial and temporal scales. In this research, we describe one possible specification of the wildfire production function, a dynamic and spatially explicit representation of annual wildfire activity.

Our version of the wildfire production function[1] relates wildfire output, W_t, to vectors of exogenous inputs $\mathbf{Z}_t$, $\mathbf{W}_{t-j}$ (a j-dimensional vector of j yr of past wildfire), and current and past levels of intervention or control variables (e.g., suppression and presuppression), $\mathbf{x}_{t-k}$. Inputs are measures of factors expected to affect aggregate wildfire activity, including fuel loads, the contiguity of vegetation, the availability of wildfire suppression resources, and climate or weather patterns. Because wildfire risk could be related to the source of ignitions, and because the mix of ignitions varies across a landscape, we specify separate wildfire functions for major categories of ignition sources. The separate specifications therefore permit the influences of the hypothesized explanatory variables to differ among the major sources, potentially providing additional insights into why wildfire patterns may vary among regions even after controlling for differences in the levels of wildfire inputs. In our analysis, the spatial unit of inference is the county.

The burned area of forest wildfire ignited by source s in county i in year t ($W_{s,i,t}$) is related to the amount of forest in the county (F_i), past levels of forest wildfire by all sources

$$W_{i,t} = \sum_{s=1}^{S} W_{s,i,t} ,$$

for j lags, a vector of current and k lags of the county's permitted traditional prescribed burning area ($\mathbf{HB}_{i,t-k}$), a vector of current and l lags of the county's permitted forest site prep plus seed prep burning area ($\mathbf{SB}_{i,t-l}$)[2] a vector of m lags of the volume of the county's pulpwood harvests ($\mathbf{P}_{i,t-m}$), housing count in the county ($H_{i,t}$), measures of underlying ecological variables (e.g., land form, potential vegetation communities, soils) of the county (Z_i)[3], and the Niño 3 SST (sea surface temperature) anomaly in degrees centigrade (E_t), a metric which indicates both the direction and magnitude of the El Niño-Southern Oscillation (ENSO). All but the ecological measures and ENSO variables are expressed relative to forest area in the county (F_i), which effectively converts the wildfire production function into a wildfire risk function.

Noting the expected direction of effect, the model is generally specified as:

$$\frac{W_{s,i,t}}{F_i} = g[\frac{\mathbf{W}_{i,t-j}}{F_i}(-), \frac{\mathbf{HB}_{i,t-k}}{F_i}(-), \frac{\mathbf{SB}_{i,t-l}}{F_i}(-), \frac{\mathbf{P}_{i,t-m}}{F_i}(-), \frac{H_{i,t}}{F_i}(\pm), Z_i(\pm), E_t(\pm)] \tag{1}$$

The expected direction of influences of the wildfire input variables shown above could be explained as follows. We expect that previous wildfires reduce current risk because previous wildfires consume flammable vegetation and create a more fragmented landscape (Miller and Urban 2000). Such fragmentation of fuels on the landscape can inhibit the spread of new wildfires, although countervailing influences are possible: fragmentation may allow fuels to dry more easily and allow stronger surface winds to develop, for example (Ranney et al. 1981). Traditional prescribed burning, site plus seed prep burning, and harvesting of small-diameter material are expected to reduce wildfire risk as long as such burning does not accidentally escape and such harvesting does not increase fuel loads. Housing could have a positive or a negative effect on wildfire risk: greater housing density might imply quicker detection, faster firefighting response capability, and greater firefighting resources applied to protect structures and people. In addition, housing is likely to be associated with breaks in fuel contiguity because of yards, roads, and other constructions, all of which could facilitate firefighting access and impede wildfire spread. Alternatively, the greater risk of accidental ignition or arson associated with development may lead to more wildfire.

The underlying ecological variables (Z) affect wildfire risks in many and sometimes counteracting ways, the net effects of which are difficult to predict. For example, the vegetation dominating the forests of some ecological zones is highly flammable and encourages wildfire spread, while other ecological zones contain standing water or agricultural development that break up fuel contiguity and slow wildfire spread.

Wildfire risk is expected to be negatively related to ENSO-induced central Pacific SST anomalies (Brenner 1991, Barnett and Brenner 1992). Because the spatial and temporal units of inference in our analysis are different from those in previous research, however, the statistical link between such anomalies and wildfire found by our study could differ. Casual observation of ENSO for the 1997–1998 fire season reveal that SST anomalies were mostly positive even though wildfire was catastrophic that year, illustrating the unusual nature of the 1997–1998 cycle (Ropelewski 1999). This cycle was dubbed Super El Niño because the positive SST anomalies were the largest in over 50 yr of accurate sea surface temperature data and larger than any observed in monthly proxy data extending back to 1856 (Woodruff et al. 1987). Its teleconnections to Florida's weather may therefore have differed from typical ENSO cycles, and for this reason we introduce a dummy variable, E_{1998}, equal to 1 in 1998 and 0 in other years, which should pick up any difference between the "typical" ENSO-wildfire relationship and that observed in 1998.

Because our data form a longitudinal series of observations for each county, we specified a fixed-effects panel data statistical model to capture individual effects characterizing the observational units (counties), effectively controlling for static county-specific factors (e.g., those contained in Z). The panel model contains an error term, $\omega_{i,t}$, associated with each observation. In the classical generalized regression model, $E[\omega_{i,t}] = 0$, $Var[\omega_{i,t}] = \sigma^2$, and $Cov[\omega_{i,t}, \omega_{j,s}] = 0$ ($i \neq j, t \neq s$). In the fixed-effects regression model, $Cov[\omega_{i,t}, \omega_{j,t}]$ ($i \neq j$) may be nonzero. Unless the cross-sectional error correlations are addressed, OLS estimation done by simply pooling time series and cross-sectional data corresponding to the variables in (1) would be inappropriate (see Greene 1990, p. 469–472). We expect, in fact, that cross-sectional error correlations could arise from correlations across units in static (in the spatial and temporal time frames considered) variables affecting wildfire. The fixed-effects panel model controls for the cross-sectional correlations by introducing a set of i dummy shifters for each county, d_i. In this framework, the effects of ecological zones identified in (1), Z, on wildfire in each county are captured by the coefficient on the dummy shifter for the county. Time series error correlations in the fixed-effects approach can be evaluated using traditional indicators (e.g., by examining the correlograms of equation residuals) and corrected by specifying a more elaborate model (Greene 1990, p. 479–480)[4].

Another factor affecting model estimation consistency is heteroscedasticity in the distribution of the residuals. We account for this by applying two estimation procedures and one data transformation. The first estimation procedure is White's method (White 1980), which accounts for errors associated with the size of explanatory variables in the model, and the second is cross-sectionally weighted least squares (see Greene 1990, p. 465–469), which accounts for groupwise (i.e., within the cross-section, the county in our case) heteroscedasticity in the error terms. The data transformation that we apply is to take the natural logarithm of each variable. The ENSO measure, which is often negative, is not transformed in this way, however.

A final source of error correlation that can produce statistical inconsistencies in estimation is spatial autocorrelation among observational units (Anselin 1988). Spatial autocorrelation exists if the errors in a cross-sectional data set are correlated across (spatially oriented) units of observation. We tested ex-post for evidence of spatial autocorrelation and found none.[5]

The specification of this model was therefore:

$$\begin{aligned}\ln\left(\frac{W_{s,i,t}}{F_i}\right) &= \sum_{i=1}^{I} a_i d_i + \sum_{j=1}^{J} b_j \ln\left(\frac{W_{i,t-j}}{F_i}\right) \\ &+ \sum_{k=0}^{K} c_k \ln\left(\frac{HB_{i,t-k}}{F_i}\right) + \sum_{l=0}^{L} e_l \ln\left(\frac{SB_{i,t-l}}{F_i}\right) \\ &+ \sum_{m=1}^{M} f_m \ln\left(\frac{P_{i,t-m}}{F_i}\right) + g_1 E_t + g_2 E_{1998} \\ &+ h \ln\left(\frac{H_{i,t}}{F_i}\right) + \omega_{i,t}\end{aligned} \tag{2}$$

This equation forces the structural relationship between wildfire area and right-hand-side variables to be identical across all counties, although the intercept-shifting county dummies allow endemic levels of wildfire to vary across counties due to, for example, the ecological zones.

Data limitations forced a compromise between information (degrees of freedom and available cross-sectional units) and risk of model inconsistency. In particular, we lacked a long series of observations on traditional prescribed burning and site plus seed prep burning. The number of lags of these variables in the estimated version of (2) was small; longer lags revealed no new insights on their effects but removed information from the data (by reducing the number of useable observations). Because a process of model selection was undertaken rather than a wholly *a priori* approach, the statistical significances should be interpreted with caution.

Data

Our analyses relied on two datasets obtained from the Florida Division of Forestry. The first contained records of all wildland fires reported to the State since 1981. This dataset included the date that the fire was first reported, the location of the fire (county, township, range, and cadastral section of its origin), the fire's dominant fuel type, and the total area burned. Because we focused on forest wildfires, wildfires whose principal fuel was classed as "grassy" were not included in the analysis.[6] Missing data on prescribed burns forced us to drop some counties from the dataset used for estimation. We also dropped 13 counties with federal landholdings; most fires on federal lands were not included in this database. Federal areas included Eglin Air Force Base, NASA's Cape Canaveral, Everglades National Park, Big Cypress Wildlife Preserve, and the National Forests of Apalachicola, Osceola, and Ocala.

A plot of forest wildfire (ha yr^{-1}) by ecoregion section (Figure 1) illustrates the variability across ecoregions. This confirms the importance of accounting for spatial differences in endemic wildfire by estimating a panel data model. Also notable in the data is the cusped nature of wildfire—high wildfire activity in one year, followed by several years of low wildfire activity.

Our second key dataset describes burn permits issued by the State of Florida. The State requires permits for open burning, valid for 1 day following their issuance. Permission may be granted to implement the burn on a later date, and such a continuance is not counted in our analysis as a new permit. The burn permit database contains one record per initial permit and includes the day of the permitted burn, a purpose code, the total burn area permitted, and the township, range, and cadastral section of at least one portion of the intended burn. The records span differing periods depending on the county, extending as far back as 1989 but with full, statewide coverage not achieved until 1993. Burn permits issued for agricultural purposes were not used, including burns of rangeland. The areas of traditional prescribed burn and site

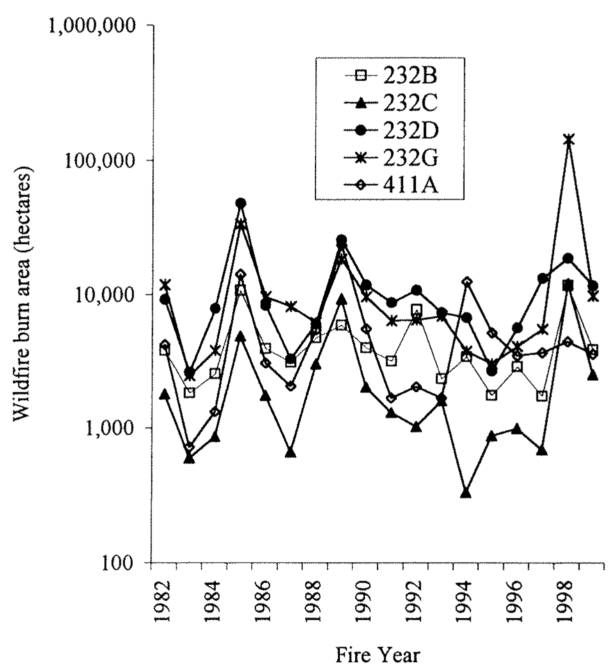

Figure 1. Wildfire area (ha) by fire year (October 1 through September 30) and ecoregion section (Bailey 1995), 1982–1999.

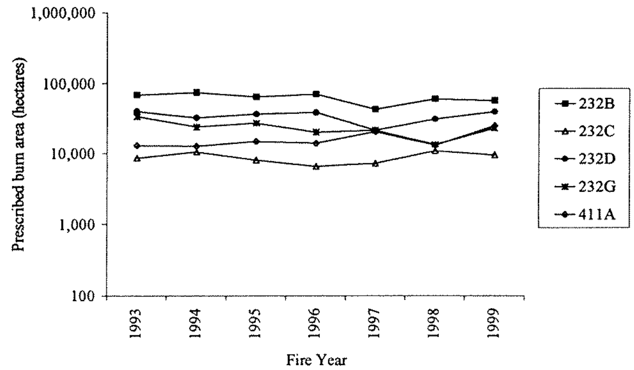

Figure 2. Area (ha yr^{-1}) for which traditional prescribed burn permits were issued, by ecoregion section (Bailey 1995). Permit data were only available statewide from 1993 to 1999.

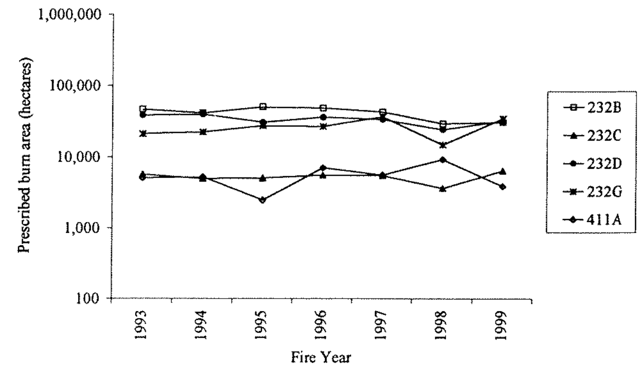

Figure 3. Area (ha yr^{-1}) for which site prep plus seed prep prescribed burn permits were issued, by ecoregion section (Bailey 1995). Permit data were only available statewide from 1993 to 1999.

plus seed prep burn permits issued are shown in Figures 2 and 3. They show that the area of prescribed burn permits in Florida is less variable and much larger on an annual basis than the area of wildfire. Prescribed burning occurred on 260,000 ha on average from 1993–1999, while wildfire in forest fuel types (Figure 1) averaged 46,000 ha annually over the same period.

Because data summaries confirmed that early fall is a slow period for both wildfires and prescribed burn permits, the fire year in our analysis ran from October 1 to September 30. Figure 4 shows that, despite some temporal overlap in current year wildfire area and current year permitted prescribed burning area, the vast majority of prescribed burning in the current year precedes wildfire in the current year. Any remaining overlap of prescribed burn and wildfire area implies that a degree of model inconsistency could appear in our equation estimate.[7]

The third set of data, pulpwood removals by county by year, was obtained from the Forest Inventory and Analysis unit of the USDA Forest Service, Knoxville, Tennessee. The pulpwood variables shown in (2) were the sum of softwood and hardwood pulpwood volume removed. Data on pulpwood harvests were available for the calendar year, not the October–September year of our analyses. Hence, because some harvests can happen during and after fires in a fire year, only lagged calendar years of pulpwood harvests were included, thereby reducing problems of simultaneity bias.

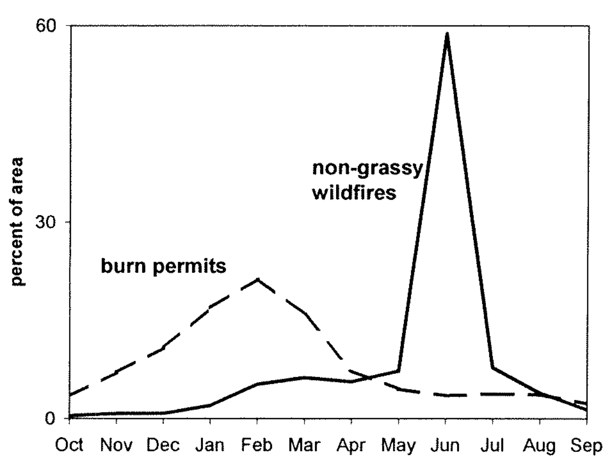

Figure 4. Percent of average annual prescribed burn permit area (sum of seed and site prep and traditional burn permits area) and percent of average annual nongrassy wildfire area occurring each month, 1993–1999. Note: data exclude sections in federal ownership.

Housing data were drawn from county-level projections (Bureau of Economic and Business Research 1999). The Florida housing data were estimated annually by county (Bureau of Economic and Business Research 1999) for 1980–1996. Housing was indexed by the stock of single- and multi-family dwellings. The Bureau of Economic and Business Research (1999) provided a county-by-county estimate of dwellings for 2000. The 2000 figure was used to linearly interpolate the number of dwellings by county for 1997, 1998, and 1999.

Monthly data on the measure of ENSO, the Niño 3 SST anomaly, were obtained from the National Oceanic and Atmospheric Administration (2000). Annual Niño 3 SST anomaly data were generated by averaging the 12 monthly observations of the Niño 3 SST anomaly over the fire year (October–September). While such an aggregate figure misses ENSO's intra-annual variability, the annual nature of our other data limited our alternatives.

Results and Discussion

Model estimates were broadly significant, yielded differences among ignition sources, and described a wildfire pattern that is highly dynamic (Table 1). Parameter estimates shown in Table 1 illustrate the differences among the all-ignitions and the ignition-specific forest wildfire risk models. The all-ignitions model explained 67% of the variation in wildfire risk by county by year. Parameter estimates show that wildfire risk in the current year was negatively related to 7 past years of wildfire. Wildfire in a county is reduced on average by 0.29 ha for each ha of wildfire occurring in any of the 7 yr preceding. The suppressive effect of past wildfire was found even when fire ignition sources were modeled separately, its effect persisting for several years. In the ignition-source specific models, 4 to 10 lags were usually negative and significantly different from 0 at the 90% confidence level or higher. In the lightning-ignited wildfire model, current wildfire is negatively related to past wildfire for up to 12 yr. Hence, it appears that past wildfire is most effective in lowering current risk of lightning-ignited wildfires and somewhat less effective for arson- and accident-ignited wildfires.

Table 1. Model parameter estimates of equations relating wildfire area relative to forest area to the ratios of past wildfire, past prescribed burning, and housing density to forest area, and of El Niño 3 sea surface temperature anomaly (Niño 3 SST), 1995–1999, all ignition sources combined, and disaggregated by three ignition sources.

Explanatory variable	All ignitions	Arson	Accidents	Lightning
ln(*Wildfire Area*$_{t-1}$/*Forest Area*)	–0.32***	–0.18**	–0.29***	–0.04
	(0.06)	(0.09)	(0.06)	(0.07)
ln(*Wildfire Area*$_{t-2}$/*Forest Area*)	–0.40***	–0.37***	–0.32***	–0.53***
	(0.07)	(0.12)	(0.06)	(0.08)
ln(*Wildfire Area*$_{t-3}$/*Forest Area*)	–0.28**	–0.27**	–0.10	–0.41***
	(0.08)	(0.11)	(0.09)	(0.13)
ln(*Wildfire Area*$_{t-4}$/*Forest Area*)	–0.39***	–0.38***	–0.25***	–0.57***
	(0.08)	(0.13)	(0.08)	(0.12)
ln(*Wildfire Area*$_{t-5}$/*Forest Area*)	–0.31***	0.08	–0.33***	–0.28**
	(0.07)	(0.10)	(0.07)	(0.13)
ln(*Wildfire Area*$_{t-6}$/*Forest Area*)	–0.16**	0.13	–0.27***	–0.42***
	(0.07)	(0.11)	(0.07)	(0.13)
ln(*Wildfire Area*$_{t-7}$/*Forest Area*)	–0.15*	–0.04	–0.22***	–0.29**
	(0.08)	(0.07)	(0.07)	(0.13)
ln(*Wildfire Area*$_{t-8}$/*Forest Area*)	0.061	0.02	–0.09	–0.13
	(0.08)	(0.11)	(0.07)	(0.13)
ln(*Wildfire Area*$_{t-9}$/*Forest Area*)	0.12	–0.12	–0.05	0.26**
	(0.07)	(0.08)	(0.07)	(0.12)
ln(*Wildfire Area*$_{t-10}$/*Forest Area*)	0.098	–0.21**	–0.03	–0.21**
	(0.06)	(0.09)	(0.06)	(0.10)
ln(*Wildfire Area*$_{t-11}$/*Forest Area*)	–0.13*	–0.15*	–0.10	–0.39***
	(0.07)	(0.09)	(0.07)	(0.08)
ln(*Wildfire Area*$_{t-12}$/*Forest Area*)	0.07	0.30***	0.03	–0.35***
	(0.05)	(0.06)	(0.04)	(0.07)
ln(*Site Plus Seed Prep Permits*$_t$/ *Forest Area*)	–0.10***	–0.15**	0.03	0.03
	(0.04)	(0.07)	(0.04)	(0.11)
ln(*Site Plus Seed Prep Permits*$_{t-1}$/*Forest Area*)	0.06*	–0.07	0.11***	0.06
	(0.04)	(0.05)	(0.04)	(0.13)
ln(*Site Plus Seed Prep Permits*$_{t-2}$/*Forest Area*)	–0.05	–0.07	–0.01	0.06
	(0.05)	(0.07)	(0.06)	(0.10)
ln(*Trad. P.B. Permits*$_t$/*Forest Area*)	–0.02	–0.07	–0.07	0.19**
	(0.05)	(0.11)	(0.08)	(0.09)
ln(*Trad. P.B. Permits*$_{t-1}$/*Forest Area*)	0.08	–0.02	0.32***	0.07
	(0.08)	(0.12)	(0.07)	(0.13)
ln(*Trad. P.B. Permits*$_{t-2}$/*Forest Area*)	–0.13	–0.19	–0.01	–0.26**
	(0.08)	(0.16)	(0.05)	(0.13)
ln(*Pulp Harvest Vol.*$_{t-1}$/*Forest Area*)	0.59***	0.84*	0.43***	–0.01
	(0.18)	(0.43)	(0.15)	(0.43)
ln(*Pulp Harvest Vol.*$_{t-2}$/*Forest Area*)	0.90***	–0.02	0.43*	1.80***
	(0.19)	(0.33)	(0.22)	(0.43)
ln(*Pulp Harvest Vol.*$_{t-3}$/*Forest Area*)	–0.57***	–0.82***	–0.38**	0.02
	(0.18)	(0.30)	(0.19)	(0.36)
Niño 3 SST$_t$ anomaly	–0.59***	–0.82***	–0.64***	–0.33**
	(0.09)	(0.16)	(0.08)	(0.14)
1998 Dummy	1.86***	1.27***	0.98***	2.18***
	(0.18)	(0.31)	(0.20)	(0.35)
ln(*Thousand Houses*$_t$ /*Forest Area*)	–0.05	0.06	1.78	4.16
	(2.06)	(3.70)	(2.68)	(3.03)
Number of cross–sections	39	39	39	39
Number of years	5	5	5	5
Total panel (unbalanced) observations	176	167	176	163
Adjusted R^2	0.67	0.47	0.62	0.62

NOTE: Asterisks indicate statistical significance at 1% (***), 5%(**), and 10%(*). Equation estimates reported here exclude the estimates of county effects (dummies), which are available from the authors. Standard errors are shown in parentheses.

Findings on the effects of the two kinds of prescribed burning varied by the kind of prescribed burning and by ignition source model. Site plus seed prep burn permits in the current year were generally negatively related to risk of wildfire, but permits from the previous year were positively related, although the effects varied by ignition source. In the all-ignitions model, each 1% increase from mean levels of permitted area for site prep plus seed prep burns was associated with an average reduction in wildfire area of about 0.1% for the current year. In contrast, permits for traditional prescribed burning were either statistically positively related to wildfire risk in the current year (at 1 to 5% significance) or were unrelated. This result was contrary to our expectations [equation (1)]. One possible explanation for these findings is that our risk function specifications might have omitted a variable that is a positive wildfire risk factor recognized by land managers and that is only sometimes addressed with traditional prescribed burning. An exception to this prescribed fire finding was a 2 yr lag for lightning-ignited wildfire, where the effect was negative.

Another possible explanation for the counterintuitive result on prescribed fire may be that our prescribed fire proxy variables (permits) were inappropriate. The use of data on burn permits in our statistical models, rather than data on actually completed burns, carries an assumption that the rate of burn permit completion is constant over time and space; failure of this assumption would mean that our model estimates would be inconsistent, although the statistical importance of this failure is unknown. This subject could be an area for further research. It also bears mentioning that the coefficients for the burn permits variables implicitly contain the rate of permit completion. For example, if 50% of permitted burns were carried out, then the actual effect of prescribed fire on wildfire area would be double the magnitude of what the parameter estimates imply.

Pulpwood harvests, our measure of small diameter materials removals, had varying effects on wildfire risk, showing complex temporal variability and influences which varied by ignition source. For the all-ignitions model, the independent effect of such harvesting was to increase the risk of wildfire. For each 1% increase in harvest, wildfire risk increased by 0.59% 1 yr following harvest and by 0.90% 2 yr after harvest, followed by a decrease of 0.57% in the third year following harvest.[8] One possibility for the inverse-U-shaped pattern of influence on wildfire is that in the first 2 yr after harvest the residual slash in partially cut stands becomes a fuel source. After 3 yr, however, enough of this residual slash is decomposed that the protective effects of a thinner litter layer and open canopy reduce overall fire risk. Coupled with our finding on the link between site and seed prep burning and wildfire, this statistical link between pulpwood harvesting and wildfire could imply that, unless all slash is removed following a harvest, pulpwood harvesting may initially increase the risk of wildfire. However, the processes of harvest, site prep, and regeneration are complex and have potentially interacting effects on fire risk. More research into this subject is needed before we can place great credence in the explanation above.

Across ignition sources, the effects of small diameter materials removals varied in direction. Arson-ignited wildfire risk is positively associated with pulpwood removals after one year and negatively after three. Accident-ignited wildfire risk is positively related to pulpwood harvests for 1 and 2 yr after the harvests, then negatively in the third. For lightning, risks were unaffected by the 1- and 3-yr lags of harvest, although they were elevated 2 yr after harvest. The results suggest that the probability of ignition is related to postharvest conditions but that the relationship differs by ignition source. We can only speculate why this occurs. For example, accidents and arson ignitions might be associated with human activities around slash piles and windrows while lightning's influence would be more equal across the site. These two parts of the site would have differing fuel dynamics over time, and this might be reflected in differing temporal patterns for the different ignition sources, but one could construct other explanations.

The Niño 3 SST anomaly and the 1998 dummy were statistically significant explainers of variation in wildfire risk in all models. However, the magnitude of the coefficients varied by ignition source. In all models, SST anomalies were negatively related to wildfire in years besides 1998, confirming the results of previous research (Brenner 1991, Barnett and Brenner 1992). The ENSO cycle of 1997–1998 was most pronounced for lightning-ignited fires and least pronounced for accidents. In 1998, lightning dominated other ignition sources, so these findings are not surprising.

The number of dwellings relative to the area of forest in a county was not related to wildfire risk in any of the estimated models. This result implies that greater risks of human-caused ignitions in more highly populated areas are offset by more effective suppression in these populated and roaded areas and because of the greater fragmentation of fuels in more urbanized settings.

A way to capture the value of the wildfire models is to map wildfire risk. Figure 5 shows how predicted forest wildfire risk in 2000 differed from mean annual forest wildfire risk for the more heavily forested northern portion of Florida. Blanks are counties for which data constraints prevented risk estimates. Counties in shades of gray or black had a predicted above-average forest wildfire risk in 2000, while stippled counties had a predicted below-average forest wildfire risk. This map shows how a swath in western Florida was at greater risk of wildfire in 2000 and how northeast Florida was at lower risk because of the high rate of wildfire there in 1998. Although the map is simple and reveals information gaps, it illustrates how wildfire risk models could be applied in practice. Information provided by such maps could be used by land managers at the beginning of the wildfire season to help determine allocations of presuppression and firefighting resources.

Conclusions

Our forest wildfire risk models produce several conclusions. First, long-term temporal dynamics are important in wildfire regimes in Florida. Therefore, information on past wildfires in a county can help predict current wildfire risk there. This suggests that the development of time-varying risk models for wildfire could prove useful for both insurance and land management planning strategies and might be possible at finer spatial scales than employed here. More concretely, combined with information on the trends of other important wildfire risk determinants, a variety of forward-looking maps of wildfire risk such as the one just described—rather than merely static or even forward-looking fuel maps—could be developed from our estimated risk functions.

Second, climate plays a major role in determining wildfire patterns in Florida, confirming previous studies (Brenner 1991, Barnett and Brenner 1992). However, our modeling effort might not have been at the best temporal scale to permit identification of the complex interactions between climate and fire in the state. Also, the statistical link to ENSO in 1998 differed from other years, and we have speculated that this difference was due to the magnitude and to the timing of central Pacific sea surface temperature changes in relation to the fire season. More temporally refined broad scale modeling—with months as

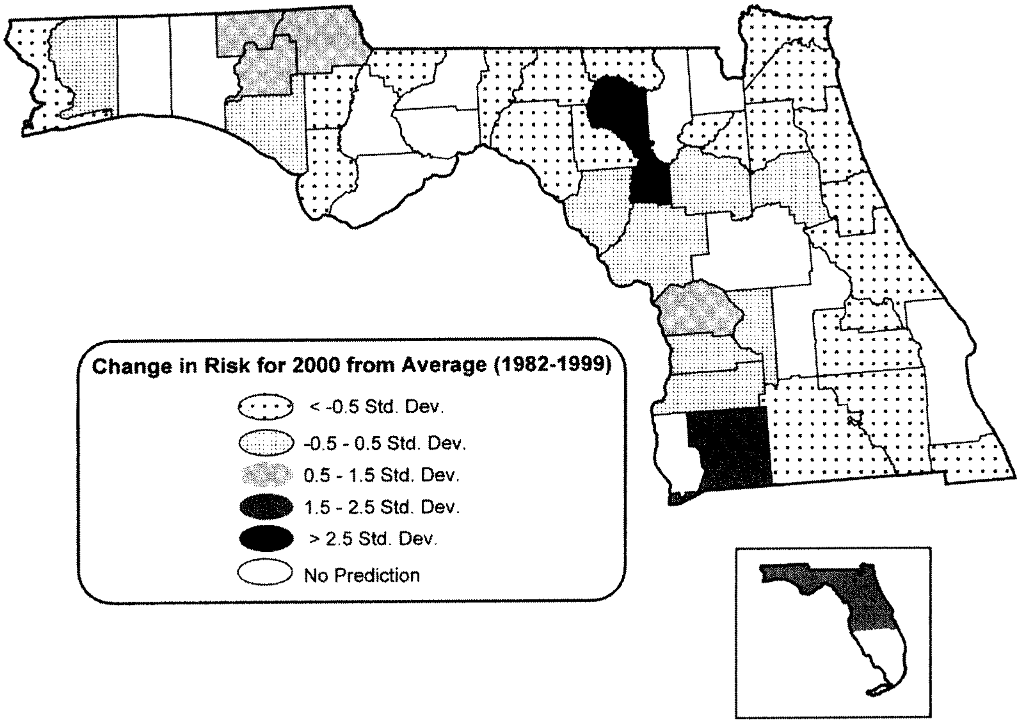

Figure 5. Change in risk by county in 2000 from the 1982–1999 average wildfire risk for the county, Florida. This map is based on the all ignition source model of wildfire risk shown in Table 1. Risk predictions for white counties were not possible, due to data limitations.

the temporal unit, for example—might reveal these relationships more fully.

Third, we identified vegetation management strategies that influenced wildfire patterns in Florida. The direction of influence of some strategies, however, was counterintuitive, highlighting the need for research that could validate this finding. Future modeling done at a different (e.g., finer) scale of observational unit could be a way to check the validity of such results. Furthermore, it is entirely possible that traditional prescribed burning reduces the intensity of wildfires, even if it does not reduce the amount of wildfire. We did not evaluate wildfire intensity in this study.

Fourth, the wildland-urban interface was identified as a statistically insignificant wildfire risk factor. Risks of economic damage from wildfire in the WUI (Butry et al. 2001), however, might be sufficient incentive to further refine our understanding of the relationship between wildfire and human factors. Future research might more successfully characterize the WUI's influence by explicitly accounting for varying road network density, the number of houses located within forests, the amount of land dedicated to agriculture, and the degree of suppression effort expended by communities, homeowners, and managers of forests.

Fifth, different ignition sources of wildfire do seem to respond differently to the long-run suppressive effect of wildfire, the effects of ENSO during a Super El Niño cycle, and the effects of vegetation management and harvesting. Hence, there might be some advantage to further exploring differences among ignition-specific wildfire risks. To the extent that the mix of ignitions varies across Florida, the differing wildfire risk functions reported here imply that the best mix of strategies to mitigate wildfire damages may vary by location.

Forest and fire management policies regarding fuel management and wildfire risk mitigation have been based on very few studies conducted at the broad temporal and spatial scales over which the policies are implemented. Such policies should be evaluated in ways that recognize the complexity of the relationships among wildfire, suppression and presuppression activities, diverse ignition risks, stochastic weather and climate, changing land use patterns, and other ecological factors. Our models represent initial steps toward quantifying these relationships, moving us closer to a goal of understanding the best approaches to wildfire intervention in wildfire prone landscapes.

Endnotes

[1] As we shall describe, our models are actually forest wildfire risk functions because we are estimating forest wildfire area divided by forest area. The distinction is not immediately important, as the transformation of risk to production is trivial.

[2] Four types of permits were recognized in the risk functions estimated here, and these four were grouped into two categories: hazard reduction and "ecology burn" permits, grouped into a category that we call "traditional prescribed burning," and site prep and prior-to-seed silvicultural burn permits, which were grouped into a category that we call "site plus seed prep burning."

[3] For example, as characterized by the amount of land in ecoregion sections, a classification scheme related to land form, soil types, potential vegetation, and climate. In Florida, there are four sections of Province 232 (B, C, D, G) and one (A) of Province 411, the Everglades. See Bailey (1995) for a description of each.

[4] No significant serial correlations were identified in our estimated models, so no additional modeling was indicated.

[5] Tests of spatial autocorrelation (Moran 1948) that examined both annual and aggregated (1994–1999) levels of error autocorrelation could not reject spatial independence (results of these tests are available from the authors). A spatial lag model of the kind recommended by Anselin (1988)

was estimated and found no significant spatial lag dependence (results also available from the authors). Spatial lag and error versions (Ord 1975, Anselin 1988) of the all-ignitions version of the wildfire risk model were derived and estimated. ArcView® (Version 3.1) and the SpaceStat™ (Version 1.90) Extension for ArcView® were used to generate the inverse-distance spatial weighting matrix needed. In those estimates, available from the authors, the time-invariant spatial lag and error parameter estimates were not statistically different from zero at 5% significance.

[6] Of course, grassy fuel fires may burn into forests or may in fact start in the midst of forests; we expect this simplification to be most important in counties where grassy fuels are predominant.

[7] Within counties, the likelihood of overlap is even smaller; often, burn permits are not offered once the wildfire season is underway in the zone of the permitting agency.

[8] Subsequent lags (4, 5, 6, 7) were not statistically related to wildfire area in the current year, at 10% significance or lower.

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